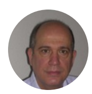
Dancing with Horses: Automated Quality Feedback for Dressage Riders

Conference Paper · January 2015

DOI: 10.1145/2750858.2807536

5 authors, including:


Robin Thompson
Newcastle University


Ilias Kyriazakis
Newcastle University


Patrick Olivier
Newcastle University


Thomas Ploetz
Newcastle University

Dancing with Horses: Automated Quality Feedback for Dressage Riders

Robin Thompson†*, Ilias Kyriazakis▲, Amey Holden†, Patrick Olivier†, Thomas Plötz†
†*Open Lab, School of Computing Science, Newcastle University.
▲School of Agriculture, Food and Rural Development, Newcastle University.
r.j.thompson3@newcastle.ac.uk

ABSTRACT
The sport of dressage has become very popular not only amongst professional athletes but increasingly also for private horse owners. In well-defined tests, rider and horse execute movements, which demonstrate the strength, endurance, and dexterity of the animal as well as the quality of the interaction between rider and horse. Whilst at a professional level intensive expert coaching to refine the skill set of horse and rider is standard, such an approach to progression is not usually viable for the large amateur population. In this paper we present a framework for automated generation of quality feedback in dressage tests. Using on-body sensing and automated measurement of key performance attributes we are able to monitor the quality of horse movements in an objective way. We validated the developed framework in a large-scale deployment study and report on the practical usefulness of automatically generated quality feedback in amateur dressage.

Author Keywords
skill assessment; activity recognition; wearable sensing; dressage; horses

ACM Classification Keywords
H.1.2. User/Machine Systems: I.5 Pattern Recognition: J.4 Social and Behavioral Sciences

INTRODUCTION
The equestrian practice of dressage is centuries old. As early as 450 BC, Athenian historian and soldier Xenophon described the "selection, care and training of horses in general" [41]. With roots as a training method for war horses, dressage has progressed and been refined to its current status as an Olympic sport [32]. In the UK alone 17 in $1,000$ people own at least one horse totalling to approximately 1m horses in the country with steady increase rates throughout the last decade(s) [7]. Similar figures have been reported internationally. The 2009-2010 AHP Equine Industry Survey states that 78% of horse owners in the US expected to increase or maintain the number of horses they owned [2]. With rising popularity of private horse ownership dressage has recently seen a surge in interest from an amateur/hobbyist perspective. Similar to professional dressage, at the amateur level riders seek to improve the condition of their horse by instilling discipline and understanding. At a professional level dressage practice is often recorded using high-end video equipment (employing costly 3-D motion capture similar to that used in medical assessment [21]) and directly monitored by professional coaches. In contrast, amateurs – although often no less ambitious – typically do not have the means and resources for continuous professional monitoring and assessment of the horse's skills and dexterity, which often results in stagnation of development, frustration, and in the worst case injuries.

In this paper we describe the development and evaluation of a framework for automatic assessment of horse movements in dressage settings. Our approach employs miniature sensing platforms (full inertial measurement units – IMUs) that are inexpensive and can be unobtrusively attached to the horse, enabling direct movement recording with little effort and practically no hindrance for either horse or rider. Furthermore, our recording and analysis system is portable, which renders it universally applicable beyond dedicated (and costly) dressage arenas. By means of automated sensor data analysis techniques, our framework is able to provide direct, accurate, and objective feedback to the amateur rider. This allows them to gain awareness of the actions of their horse and of how they ride together, without the requirement of expensive equipment and external feedback. As such our approach is directly accessible for riders at all levels.

The contribution of this paper is three-fold: *i)* We describe the principles of dressage riding and judgment, and, based on this, specify a framework for automated skill assessment that is based on minimal alteration of established training procedures at the amateur/hobbyist level. We focus on optimising the level of detail that can be provided for automated quality feedback using an unobtrusive and inexpensive recording and analysis approach that allows amateur riders to effectively review their training and improve accordingly. *ii)* We present the movement recording and analysis system that we developed based on the specifications in *i)*. The system revolves around the use of wireless inertial measurement units (IMUs) [5] strapped to each of the horse's legs to measure acceleration and orientation of the horse's legs in a performance setting. Gait is classified and relevant performance metrics are extracted describing attributes relating to various as-

UbiComp '15, September 7-11, 2015, Osaka, Japan

DOI: http://dx.doi.org/10.1145/2750858.2807536

Level	Description
1 – Introductory	Basic gaits, and turns.
2 – Preliminary	Develops skills, training and musculature to perform the advanced level movements .
3 – Novice	Improves suppleness, balance and throughness. Introduces 15m circles.
4 – Elementary	Introduces collected work. More critical judgement.
5 – Medium	Determines the horses ability to perform medium and extended paces.
6 – Advanced Med.	Increases complexity of movements including zig-zags and five loop serpentines.
7 – Advanced	Introduces walking half-priouettes, multiple flying-lead changes and canter quarter pirouettes.
8 – Prix St. Georges	Riders are expected to show distinct differences within the gaits from collection to extension.
9 – Intermed. I	Mental and physical preparation for Intermediate II.
10 – Intermed. II	Develops the horse for the advanced skills needed for Grand Prix.
11 – Grand Prix	The most advanced and complicated movements must be performed with absolute attention to detail.

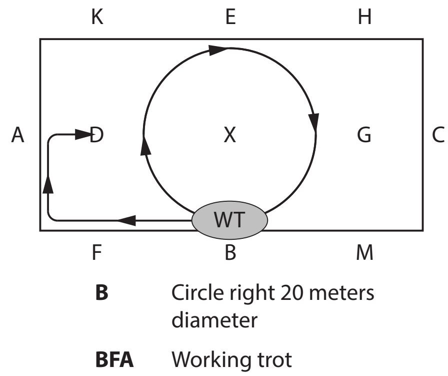


Figure 1: Overview of the dressage assessment procedures with the eleven levels of competitions (left), and an example of a dressage movement (right). Representing a birds-eye view of the dressage arena, the letters around the circumference represent physical plaques that act as an indication of location for the rider. The solid line with arrows represents the desired path of the horse, and the letters in the ellipse indicate a gait transition, in this case to a working trot.

pects of the training scale, and can be interpreted by riders to identify areas for improvement. *iii)* We evaluate the applicability and the practical value of our automated assessment system in a large-scale deployment with 21 riders and 23 horses being assessed in standard dressage exercises. We demonstrate the practical value of the developed framework for automatically tracking key performance attributes that are of relevance for providing objective feedback on the quality of dressage movements. We show that the system produces precise feedback as we extract key, objective attributes from the performance, enhancing a rider's ability to learn from their mistakes. As such the developed framework has the potential to be of substantial practical value for the large population of dressage hobbyists.

DRESSAGE AND JUDGMENT

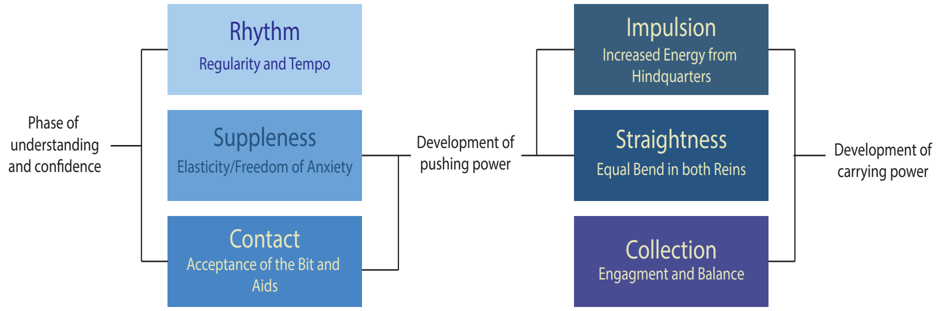
The horse's natural speed and endurance are a result of their role as a prey species within the ecology of the North American prairies, supplemented by a significant amount of selective breeding and training by humans [15]. Through development and conditioning it has been possible to train horses to display tremendous precision and dexterity, allowing these half ton animals to move with the utmost grace across an arena. No differently from human athletes, a horse's body and its condition are crucial to reaching the highest levels of performance. Training induces physiological adaptations that allow the horse to perform at a high level with minimal risk of injury [15]. During dressage tests it has been shown that the horse reaches heart rates of up to 141 bpm [11]; in comparison to the natural resting heart rate of approximately 36 bpm, this demonstrates the exertion involved. It has been shown that it is possible to change the physiological characteristics of the dressage horse's motion through training.

Whether ridden competitively or for pleasure, dressage has been shown to have physical benefits for both the riders and the horses [15]. As a sport, dressage is performed through the execution of "tests": predefined sequences of movements of varying difficulty linked together with transitionary movements. Depending on the experience and ability of the horse and rider, different levels of dressage are performed. These range from "Introductory", the most rudimentary of exercises, to "Grand Prix", the pinnacle of the sport and the most involved and complicated exercises. The full range of levels is shown in Fig. 1 (left). The same figure also illustrates an example of a movement specification as it would be presented to a rider (right). This represents a top down view of the dressage arena and the horse's expected path. The letters around the circumference of the arena are representations of plaques placed around the arena that give signal to the rider regarding their location. Instructions are presented in terms of locations at which movements should start and finish, and where key transitions should be made.

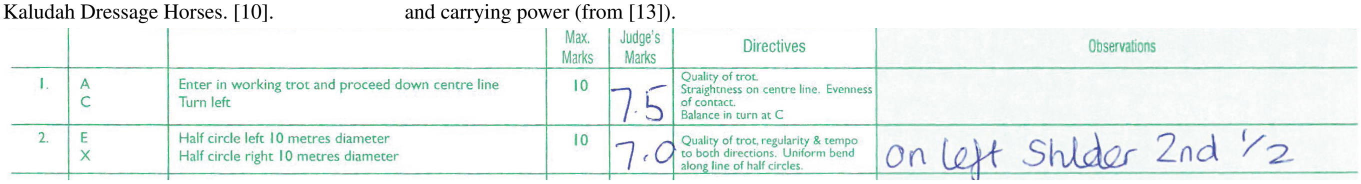
The skills required by a horse to perform dressage movements vary depending on the movement. Amongst the various basic gaits – walk, trot, and canter – regardless of the level of collection or extension required, regularity of pace and rhythm are key, as well as an ability to remain relaxed and concentrated under the pressure of performing. In turns and corners conformation to a specified line must be shown across the entire length of the horse's body. More complicated movements demand a commensurate level of skill to perform. A movement epitomising the dexterity and control required by the performing horse is the "piaffe", a trot in place, in which alternating diagonal pairs of legs are raised off the ground (Fig. 2a). This requires intense training and great amounts of strength and control on behalf of the horse, but should, nevertheless, appear effortless [32]. Progress through the levels of dressage requires conformity to the "Training Scale". As shown in Fig. 2b, there are six discrete principles of dressage which together describe the "throughness", or "Durchlässigkeit" (German; official dressage term for *throughness*) of the horse.

Throughness is a core component of judging quality in dressage, and is extremely difficult to quantify. It can be described as the connection from the bit to the hind leg, with the horse accepting the contact with submission and relaxation. The FEI judge's handbook [13] identifies the horse's confid-

(a) *Piaffe* – photo courtesy of North Kaludah Dressage Horses. [10].



(b) The training scale of dressage describing the three main phases of training: understanding, pushing power, and carrying power (from [13]).



			Max. Marks	Judge's Marks	Directives	Observations
1.	A C	Enter in working trot and proceed down centre line Turn left	10	7.5	Quality of trot. Straightness on centre line. Evenness of contact. Balance in turn at C	
2.	E X	Half circle left 10 metres diameter Half circle right 10 metres diameter	10	7.0	Quality of trot, regularity & tempo to both directions. Uniform bend along line of half circles.	on left Shlder 2nd 1/2

(c) Dressage score sheet.

Figure 2: Skill assessment in professional level dressage. (a): Rider and horse demonstrating a *piaffe*, an advanced dressage movement involving raising diagonal pairs of legs alternately whilst staying in the same place, requiring intense strength, coordination and discipline from the horse. (b): As the horse gains experience and competence at each level of the training scale attention can be paid to the next, and the horse can advance through the levels of dressage. Taken as a whole these skills contribute to the overall throughness ("Durchlässigkeit" [13]) of a horse. (c): British Dressage score sheet, completed by a qualified judge.

ence and understanding of the riders intention as fundamental aspects of *throughness*. The handbook suggests that these aspects can be be developed by training in rhythm, suppleness, and contact. Fig. 2c depicts an extract from a scoresheet as it is used in official British Dressage competitions.

At a competitive level, the quality of a horse's performance is traditionally determined by a judge. During competition, a qualified judge conducts an assessment based on a set of rules provided by the FEI (International Federation of Equestrian Sports), and informed by experience, intuition and ideals of grace and elegance of form. Through practice and routine, it is possible for a rider to develop an intuition for their, and their horse's, performance. However, for the majority of amateur riders, when not in a competition, feedback is provided by a coach or trainer. These professionally qualified individuals, often riders themselves, are able to provide feedback based on their experience and understanding of the sport. The constraints of time and money, however, place restrictions on the amount of formal coaching that an individual can receive.

AUTOMATED QUALITY FEEDBACK FOR DRESSAGE

It is the goal of our work to develop a framework for objective quality feedback for hobby dressage riders that is: *i)* ubiquitously accessible, i.e., does not rely on substantial hardware installations (as it is the case, e.g., for high-end 3-D motion capture [39]); *ii)* easy to deploy and to use even by (technically) lay users; and *iii)* that produces understandable, i.e., intelligible and accurate assessments, which provide dedicated feedback that the rider can use in order to improve their handling of the horse and thus to improve the dressage performance of horse and rider. Fig. 3 gives an overview of our recording and assessment framework.

From the outset of our development we discarded camera based sensing solutions even though video seems to be a suitable sensing modality. Reasons for this include large installation costs, limitations to indoor scenarios, and problems with occlusions that render camera-based approaches impractical for hobbyist use. Rather, we opted for a direct movement recording approach in which we strap miniature inertial measurement units (IMUs, consisting of tri-axial accelerometers, gyroscopes, and magnetometers) to the shins of the horses. It is worth mentioning that the horses are used to wearing shin-protectors in order to prevent injuries. Consequently, it is straightforward and comes with very little extra effort to secure the sensing platforms to the horse's legs (Fig. 3, we integrated the IMUs into a set of ordinary and regularly used brushing boots). We chose the four limbs for movement sensing as their characteristic movements are relevant for the majority of dressage tests. We use off-the-shelf IMUs (Axivity WAX9 [5]), which are inexpensive, robust, and come with a very small form factor (Fig. 3 – left). These four IMUs stream their sensor data to a smartphone, which the rider carries in their pocket or on an armband, that is equipped with a bespoke application capable of synchronising and storing the raw sensor data. Subsequent movement analysis is currently performed offline, i.e., after downloading the data from the smartphone. This is, however, solely because at this stage of our research we focus on the fundamental system development.

Automated assessment of dressage movements is based on the measurement of *five* fundamental performance attributes: *i)* Rhythm; *ii)* Regularity; *iii)* Impulsion; *iv)* Consistency of duty factor; and *v)* Smoothness of turns and straights. These attributes mirror guidance provided to professional judges on how they should assess the quality of dressage movements (according to the FEI official judge's handbook [13]). Whilst

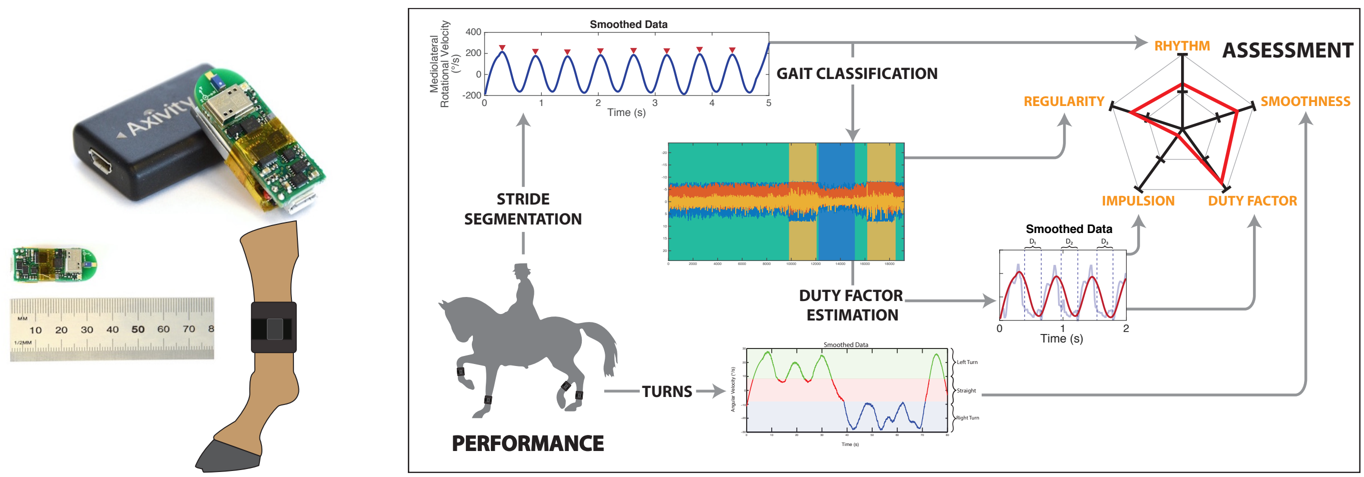


Figure 3: Overview of the sensing and analysis framework for automated generation of quality feedback for dressage riders. Left: Miniature sensing platforms (IMUs; axivity's WAX9 [5]) are incorporated into a set of brushing boots. The boots are strapped around the horses cannon bone, above the fetlock. The boots used in the study were made of neoprene with velcro fastenings, meaning they were flexible and comfortable whilst maintaining a secure position. Right: Analysis workflow that measures five distinct performance attributes as they are of relevance for dressage assessment (see text for description).

many of the judging attributes are somewhat subjective, we have extracted core, objective aspects of each from measurement as described below. It is our goal to provide objective feedback to the rider and as such we concentrate on aforementioned quality parameters. The above terms are described in more detail and in the context of our system in the section titled "Identifying Performance Attributes" below.

Our framework follows a linear work flow (Fig. 3 – right). The horse's strides are automatically segmented across the whole session. This segmentation forms the basis for several of our performance attributes, as it describes the first tier on the training scale at a very low level. Stride segmentation also provides the foundation for the subsequent gait classification. Assessment of performance attributes is then pursued per movement (definition given below) and results are visualised in form of spider plots as depicted in the figure.

In what follows we will describe the performance attributes we have identified and the technical procedures for measuring them. The basis for these are synchronised streams of data from the three individual sensors incorporated into each of the four IMUs used. As each sensor (accelerometer, gyroscope, and magnetometer) measures on 3 axes this results in 36-dimensional input data. In the course of the study, however, we determined that in order to remain useful the magnetometer would require more calibration than it was reasonable to expect a layman to perform, and, as a result, the magnetometer data was not used. Subsequently all analysis was performed on 24-D sensor data recorded with a sampling rate of 80Hz (as supported by the sensors per default).

For most of the measurement procedures described below, we use a sliding window approach that analyses sensor data in their temporal context. This is motivated by the inherent sequential nature of the data for which a singular treatment is typically not insightful. Based on informal cross-validation experiments we optimised the window length to 3 seconds, i.e., with aforementioned sampling rate analysing 240 consecutive sensor readings, as this allows the slowest typical gait – walk – to cycle fully twice and thus to capture all relevant characteristics in one analysis frame (for a horse of average build). Subsequent analysis frames overlap by 90% in order to maintain a suitable temporal resolution of the extracted attributes. In the remainder we will refer to the horses' legs by FR, FL, BR, and BL, where F and B indicate fore and back legs, and L and R indicate left and right.

Pre-processing: Segmentation

Our dressage assessment system operates directly on the raw IMU sensor data in the sense that we measure dedicated performance attributes (as described below) for feedback generation. Effective calculation of these measures requires some elementary pre-processing steps: *i)* stride delimitation; *ii)* gait classification; and *iii)* movement segmentation. Before describing the measurement of the actual performance attributes we will first summarise these pre-processing steps.

Stride Delimitation

We segment individual strides – per limb – based on peak-detection within the smoothed mediolateral axis of the gyroscope. The mediolateral axis refers to the axis that runs from the centre of the horse to the flank parallel to the floor, see Fig. 5. When considered in the context of the sensor's locations on the leg, the gyroscope data in this axis describes the leg's swing forwards and back as each stride is made. The peaks in this data stream describe the points at which the rotational velocity is largest, that is, when the leg is swinging forward fastest. This occurs at a consistent point in each stride and consequently can be used as a stride delimiter. Noise in the signal can cause confusion when using peak finding algorithms. Accordingly, we use a lowpass Butterworth filter in order to remove the majority of the noise, followed by a Savitzky-Golay filter to clean up the resulting signal. Fig. 4 illustrates the typical gyroscope signal for a single sensor during a trot with clear peaks per stride. Information about strides (and sequences thereof) are required for measuring a number of the performance attributes as described below.

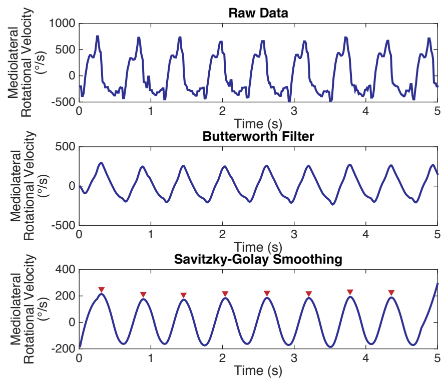


Figure 4: The stages of noise removal as mediolateral gyroscope data is pre-processed for stride delimitation. The red arrows in the final image indicate the positions of the stride delimiting peaks.

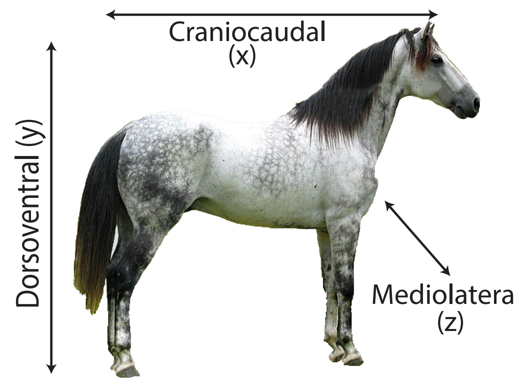


Figure 5: The three axes of the IMU in the context of the horse's body. The x-axis describes movement in the axis running from the head to the tail of the horse (craniocaudal). The y-axis describes movement in the axis running from the hooves to the back of the horse (dorsoventral). The z-axis describes movement in the axis running across the horse from one side to the other (mediolateral). Image adapted from original by Bill Vidigal '- CC-BY-SA 2.5

Gait classification

The execution of preliminary level dressage tests requires demonstration of the three main gaits: walk; trot; and canter. In order to assess these gaits using the quality parameters explained below, an automatic analysis system needs to classify gaits accordingly and with high reliability. In general the gait of a quadruped is – by nature – very regular and due to the complexity of coordinating four limbs there are quite significant differences between different gaits, which is somewhat in contrast to human gait. It allows us to perform gait classification solely based on timing analysis using simple thresholding methods. Without practical limitation we restrict gait classification to a horse's left foreleg.

Movement Segmentation

Strictly speaking there is no technical need for limiting our measurements to certain dedicated and fixed intervals as we could calculate and provide feedback continuously. However, in order to structure the generated feedback in a meaningful way we aggregate the assessments on a per-*movement* basis, which is according to the general practice of professional judges who score dressage performance in a similar way (cf. Fig. 2c for an illustration of a judge scoresheet). Movements are defined as a predetermined sequence of gaits, transitions and the path the horse should follow (cf. Fig. 1 (right)). As such, indicators for changes in movements – and hence "natural" segmentation points – are: *i)* changes in gait (e.g., from trot to canter); *ii)* changes in the horse's main orientation (e.g, when taking a turn); and *iii)* halting points. Technically, movement segmentation is straightforward and can be implemented with simple heuristics based on the aforementioned pre-processing.

Identifying Performance Attributes

As illustrated in Fig. 2b, according to professional standards, dressage judgment is essentially based on the measurement of six fundamental aspects: *i)* Rhythm; *ii)* Suppleness; *iii)* Contact; *iv)* Impulsion; *v)* Straightness; and *vi)* Collection. These categories describe the training scale of dressage. For example, mastery of Rhythm allows for training in Suppleness. Ideally a system for feedback would provide coverage for all of the rungs on this ladder, however given the sensing modality used for this framework we have selected a few key features to focus on. These features quantify the motion of the horse's legs. The elements of the training scale that are not covered by our framework either rely on a more subjective assessment, as freedom and submission do, or refer to movement that cannot be captured by sensors on the legs. We considered the restriction of sensors to the legs to be critical to the unobtrusiveness of the system, and to minimising the imposition caused to the horse. As such we have extracted the key, measurable aspects of the training scale that are displayed through the movement of the legs and interpret them in the context of the sensed data. Below is a brief description of the performance attributes we have identified and how they relate to the judged metrics.

Rhythm

The term rhythm, in this context, refers to the consistency of the beat in all paces [13]. The rate at which each of the horse's feet contact the ground should be maintained through all turns, transitions, corners and straight lines. The rate is referred to as the Tempo and is measured in beats per minute (bpm), the calculation of which is required for the calculation of the rhythm.

Regularity

Each of the three major gait classes – walk, trot, and canter – has a prescribed sequence of footfalls involving all four legs of the horse that fundamentally characterises the gait. Correct conformation to this sequence is critical if a horse is to perform at any level. Deviation from these sequences – referred to as *irregularity* – during a competition would result in the attribution of an error penalty. Consequently, *regularity*, i.e., the adherence to a prescribed footfall sequence, is an important assessment parameter for dressage judgment. We choose to use the term *Regularity* to describe this attribute in this study, as we are measuring the degree of deviation from the regular gait.

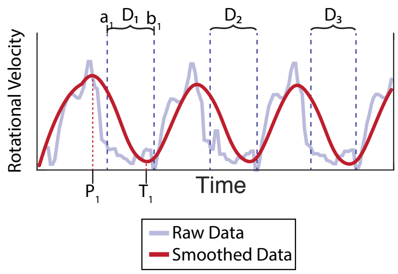


Figure 7: Illustration of stance phases (e.g., for estimation of consistency duty factor – see text for description).

Consistency of Duty Factor

The duty factor of a gait is the proportion of time in which the leg is on the ground [40]. In a similar vein to the rhythm, the metric extracted from the duty factor relates to the consistency of the gait. Given that a stride can be broken into two distinct phases, the stance phase, in which the hoof is in contact with the floor, and the stride phase, in which it is not, we are able to assess the consistency of the paces with relation to these two phases in addition to the higher level rhythm. At the higher levels of dressage performance there are generally three variants of each of the three gaits, "extended", "medium", and "collected". These variants describe a wealth of subtle variation in the gaits, but can be boiled down to a continuum between an extended gait with long reaching strides in which the horse covers as much ground as possible, and the collected gait, in which the horse's strides are short and snappy, with the maximum engagement of the hindquarters. At the lower levels of dressage the horse is not expected to perform these variations, but it is expected that the gait remain consistent in terms of the extension.

Impulsion

The impulsion of the horse is described in the literature as "increased energy from the hindquarters". The FEI judge's handbook notes that "the most important criteria of impulsion is the time the horse spends in the air rather than on the ground" [13]. This metric is only calculated for those gaits in which a phase of suspension is present i.e., trot and canter.

Smoothness of Turn and Straight

A horse should execute a turn, be it a circle or a corner, smoothly and with a uniform amount of rotation for the duration of the turn. This produces the correctly shaped turns, ensuring cleanness of corners and roundness of circles and half circles. Similarly in a straight the horse's heading should remain constant right up to the beginning of the next turn.

Calculating Performance Attributes

Rhythm

Rhythm and tempo T calculations as described in the following are conducted individually per limb. For overall skill assessment we then use averaged values across all four legs. Using our sliding window approach (window length of 3 seconds with a 90% overlap), the tempo T_m of each movement m is calculated as follows. Given a window w of N consecutive data samples that cover a series of $N_{\mathbf{P}}$ stride peaks $\mathbf{P} = \{P_1, P_2, ..., P_n\}$ derived using the technique described above (typically $N_{\mathbf{P}} \ll N$), the tempo T_w for a window w (in bpm) is calculated as:

$$T_w = \frac{\mathbf{card}(\mathbf{P})}{N * Fs * 60} = \frac{N_{\mathbf{P}}}{N * Fs * 60} \tag{1}$$

where Fs is the sampling rate in Hz. This calculation is repeated for every window w of the movement (total: W). It provides us with a set of W Tempo values for the movement m, which is under assessment:

$$\mathbf{T_m} = \{T_1, T_2, \ldots, T_W\} \tag{2}$$

where W represents the number of sliding windows covered by the movement m. The overall rhythm score R_m for the movement m is subsequently calculated as the standard deviation σ of a movement's tempo:

$$R_m = \sigma(\mathbf{T_m}) \tag{3}$$

Regularity

An ideal sequence of footfalls is created $ideal$, of the same length N, as the session being assessed $actual$. The assessment outcome is equal to the number of steps that are out of sequence. For assessment of the walk the sequence is straight-forward, as the footfalls are all simply sequential. However, for the trot and canter, gaits in which simultaneous footfalls are the ideal, a slightly different approach is required. Using a technique inspired by the substitution matrices used in bioinformatics sequence alignment [12], a substitution matrix has been built for each of the gaits.

We measure (ir-)regularity by aligning actual footfall sequences – as extracted during pre-processing using stride delimitation and gait classification – to the sequence considered ideal for the particular gaits. For a walk the ideal footfall sequence is BR – FR – BL – FL, whereas for left canter it is BL – BR & FL (simultaneously) – FR (BR – BL & FR – FL for right canter), and for trot it is FL & BR – FR & BL. We employ straightforward sequence alignment (cf, e.g., [12]) in order to detect mismatches between actual and ideal footfall sequences. We use substitution matrices with binary costs, i.e., 1 for an incorrect footfall and 0 for an acceptable footfall, allowing for reordering of simultaneous footfalls (Fig. 6) for quantifying (ir-)regularities within a movement. For a sequence of $N_{\mathbf{P}}$ footfalls (within a movement m, previously classified as gait g) regularity $E_m(g)[0 \ldots 1]$ is defined as:

$$E_m(g) = 1 - \left(\frac{1}{N_{\mathbf{P}_m}} \sum_{i=1}^{N_{\mathbf{P}_m}} \mathbf{S}_g(\text{ideal}_i, \text{actual}_i) \right) \tag{4}$$

with $\mathbf{S}_g(\text{ideal}_i, \text{actual}_i)$ denoting the element of the substitution matrix according to the ideal and the actual footfall (and $N_{\mathbf{P}_m}$ the number of strides extracted for a movement m).

Consistency of Duty Factor

Fig. 7 illustrates the signal of the mediolateral axis of a gyroscope attached to a horse's leg. Raw data are depicted by the pale blue curve. The red curve is the result of our smoothing procedure. The stance phase is the period when the horses hoof is on the floor, which in the smoothed data corresponds to the period between a peak (e.g., P_1^t) and the subsequent

$$\mathbf{S}_w = \begin{array}{c c} & \begin{array}{cccc} fl & bl & fr & br \end{array} \\ \begin{array}{c} fl \\ bl \\ fr \\ br \end{array} & \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

(a) Walk

$$\mathbf{S}_t = \begin{array}{c c} & \begin{array}{cccc} fl & bl & fr & br \end{array} \\ \begin{array}{c} fl \\ bl \\ fr \\ br \end{array} & \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

(b) Trot

$$\mathbf{S}_{lc} = \begin{array}{c c} & \begin{array}{cccc} fl & bl & fr & br \end{array} \\ \begin{array}{c} fl \\ bl \\ fr \\ br \end{array} & \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

(c) Left canter

$$\mathbf{S}_{rc} = \begin{array}{c c} & \begin{array}{cccc} fl & bl & fr & br \end{array} \\ \begin{array}{c} fl \\ bl \\ fr \\ br \end{array} & \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

(d) Right canter

Figure 6: Substitution matrices with binary costs for regularity assessments in four relevant gait types ((a) – (d)).

trough (T_1^t). Through peak and trough detection in gyroscope data, which leads to a series of indices for both – $\mathbf{P}^t$ and $\mathbf{T}^t$ – we determine beginning and end points for individual stance phases D_i as follows (superscript t indicating that we are operating on indices of the signal rather than sensor values):

$$a_i = P_i^t + (T_i^t - P_i^t) * \alpha \quad (5)$$
$$b_i = T_i^t + (T_i^t - P_i^t) * \beta \quad (6)$$

where α and β are correction coefficients that take into account the different characteristics produced by the fore and hind legs to accurately demark the hoof up and down points. By performing a grid search across these parameters, values of $\alpha = 0.09$ and $\beta = 0.18$ were found to be most accurate for fore leg readings, whilst $\alpha = 0.32$ and $\beta = 0.64$ were used for hind leg readings.

Then the length of an individual stance phase D_i is determined by $b_i - a_i$. Subsequently the consistency of the length of stance (or alternatively the consistency of the duty factor) C_m is calculated as standard deviation σ of the lengths of all N stance phases in one movement (averaged over all four legs):

$$C_m = \sigma\left(\{(b_i - a_i) | i = 1 \dots N\}\right) \quad (7)$$

Impulsion

Using the calculations described in the estimation of duty factor, i.e., essentially, through identifying the periods $FL_{up}, FR_{up}, BL_{up}, BR_{up}$ between stride peaks, we identify those periods S [in number of samples] in the gait in which all legs are suspended above the ground:

$$S = \{FL_{up} \cap FR_{up} \cap BL_{up} \cap BR_{up}\}. \quad (8)$$

Given that a more pronounced period of suspension is considered beneficial, we assume that a larger proportion of time during the gait in which all legs are off the ground is better. Consequently, the impulsion attribution (per movement) is given by:

$$I_m = \frac{\mathbf{card}(S)}{N_m} \quad (9)$$

where N_m is the number of sensor readings for the movement m being assessed.

Smoothness of Turn and Straight

Given that the dorsoventral axis (Y axis on our sensors) of the gyroscope gives us the rotational velocity with which the horse is turning we infer that its variance is indicative of the consistency of the turn or straight. Defining the time-series of dorsoventral rotational velocity data $X_{leg} = \{x_1, x_2, ..., x_{N_m}\}$ for each leg, where N_m is the number of samples for the assessed movement, we define the average rotational velocity $\tilde{H}_m$ of all four legs (for a particular movement m) as follows:

$$\tilde{H}_m = \frac{1}{N_m}\sum_{i=1}^{N_m} H_m = \frac{1}{N_m}\sum_{i=1}^{N_m}(X_{\text{FL}} + X_{\text{BL}} + X_{\text{FR}} + X_{\text{BR}}) \quad (10)$$

Smoothness S_m is defined as standard deviation σ of H_m:

$$S_m = \sigma(H_m). \quad (11)$$

Summary

To summarise, our assessment approach is based on the analysis of raw sensor data as they are recorded by the leg-worn sensing platforms. Stride delimitation based on peak detection in (pre-processed) gyroscope data leads to segmentation of movement data into strides. The extracted sequence of footfalls is then analysed regarding timing and sequentiality for gait classification in order to discriminate between the three main gaits: walk; trot; and canter. With this information we then extract performance attributes from all sensor data, i.e., analysing 24-D sensor streams as generated by the four IMUs worn by the horse (4 × tri-axial accelerometers and gyroscopes). Fig. 8 gives a visual illustration of how these attributes are calculated. For every assessed movement m we derive a 5-tuple $\mathcal{Q}_m$ that quantifies the key performance attributes as defined above:

$$\mathcal{Q}_m = [R_m, E_m, C_m, I_m, S_m]^T. \quad (12)$$

With this quantitative representation it is now possible to perform dressage assessment and to provide direct feedback to the rider as we demonstrate in the next section.

DEPLOYMENT STUDY

The sensing and analysis framework described in the previous sections offers a practical means for automatically generating direct quality feedback for dressage riders. This can be used for reflection and optimisation of training procedures and thus, eventually, for targeted improvements of the capabilities of rider and horse. Whilst our framework is generic and thus usable for all levels of horses and riders, we specifically focus on amateur and hobbyist level as that cohort represents a significant proportion for which, so far, detailed feedback is not as widely available as it is, for example, at the professional level where coaching and high-end recording equipment is accessible for individual riders on a regular

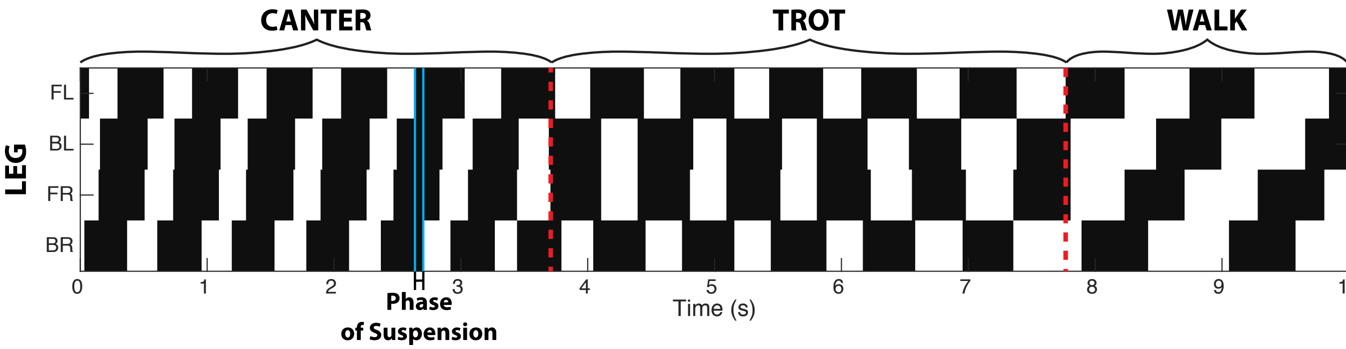


Figure 8: Generated automatically, this figure represents the periods when the horse's hooves are on the ground (white) and in the air (black). The data covered by the figure involves all three gaits, and the regularity can be clearly seen. It is interesting to note that the small differences in the timings of the stance phases for simultaneous landings can be observed in this figure. The *impulsion* attribute can be seen highlighted in cyan, during the canter phase (labeled as "Phase of Suspension"). This solid black region stretching from top to bottom describes the period which no hoof is in contact with the ground.

basis. In order to validate the practical value of our framework we used it in a large scale deployment where amateur riders participated in friendly competitions. In what follows we describe the details of this deployment and discuss the practical value of automatically generated quality feedback.

Data collection

We reached out to local horse riding clubs where dressage is regularly being practiced and recorded data for a total of 29 dressage tests that varied in the ability of the horse and rider, the difficulty level of the test and the type of horse being ridden. These tests were ridden outdoors in regular arenas, i.e., fenced areas typically used for horse riding practice. We equipped participating horses with the sensing equipment as described earlier (one WAX9 IMU for every leg of the horse, integrated into their brushing boots). Riders carried an LG Nexus 5 smartphone with our bespoke recording app running, which synchronised and stored IMU data received via bluetooth. Each test ridden was filmed to allow for subsequent annotation of the data. The data was annotated for gait, turns, and movements, by people who were familiar with the data collection process and who had an understanding of the variances of the ridden tests. The video data was distributed to several qualified judges who scored the tests performed as if in a competition setting.

Over two recording sessions we recruited a total of 23 different horses that were ridden by 21 different riders across 5 levels of dressage. The dataset contains 19 preliminary tests, and 10 tests at higher levels (cf. Fig. 1 – left). Tab. 1 summarises the characteristics of the recorded dataset.

Methodology

Our technical validation focusses on two relevant aspects:

Preprocessing Procedures

We evaluate the reliability of the automated pre-processing steps that are required for the subsequent measurements of the five performance attributes as described in the previous section. Specifically we report quantitative results – in terms of F1-scores that resemble precision and recall values as typically required for such assessments [36] – for stride segmentation, gait classification. Note that movement segmentation can be considered straightforward as it is based on predefined rules and a quantitative evaluation would simply replicate these very rules and we thus do not show results here.

Performance Attributes

The main goal of our work is to provide automated quality feedback to dressage riders. The key for an objective system of feedback is the five performance attributes we extract automatically from movement data of the horse: rhythm, regularity, consistency of duty factor, impulsion, and smoothness in turn and straight. We visualise these key attributes – and the development of their values throughout the course of an assessed dressage test – using normalised spider plots. These provide direct overviews of all five parameters in an easily graspable way and thus give direct access to quality information. Furthermore, they allow us to compare dressage tests at various levels of granularity, e.g., at the full test scale or at the level of individual (sub-) movements. We analyse the whole of the dataset recorded during our deployment study using these 5-D spider plots.

Results

Our extracted performance attributes, extracted for across whole tests, were used as features to train a classifier to predict the level of the performance. Using a SVM-based classification backend (with RBF kernel, and parameters optimised using standard grid search) technique [37], we were able to predict the level of the test performed (Preliminary, Novice, Elementary etc.) from our attributes with $> 75\%$ accuracy. The class weighted F-score was 0.76, with a class weighted precision of 0.77 and recall of 0.75. The confusion matrix describing the output can be seen in Fig 9.

This gives an indication that the metrics are discriminative with relation to the level of the horse. Classification for each gait – *walk*, *trot*, and *canter* – produced F-Measures of 0.95, 0.95 and 0.92 respectively. The weighted F-measure for all classes was 0.94.

Table 1: Overview of the dataset recorded during our deployment study.

demographics			
# riders		# horses	# tests ridden
21		23	29
data			
total: 29 tests			
total dur.: 2.12h / avg. dur. (std.): 4.37m ($\pm$35.3s))			
#prel. 4	#prel. 18	#novice	#elementary
10	9	4	6
44.3m	33.8m	18.1m	30.8m

To visualise our attributes in a way that would allow for direct comparison, we created normalised spider plots, in which smaller areas under the lines represented better assessments. In order to compare horses, the assessments were performed across the tests as a whole. To allow for comparison these assessments were grouped according to the tests that were run. This was aimed at reducing the amount of variation caused by some tests having a higher proportion of more difficult or easy movements. The resulting visualisations can be see in Fig 10. These visualisations give an indication of the variability of the assessments, between the performances, within the tests. We extracted descriptive statistics relating to the range of scores for each of these tests. The two Preliminary tests show a higher variability in the Rhythm attribute, with a standard deviation of 0.33 and 0.47 respectively, compared to 0.14 and 0.23 for Novice and Elementary respectively. Similarly for the smoothness of turns and straights, the Elementary level riders were more consistent with a standard deviation of 0.046 compared to the lower levels that were all over 0.06. This describes the trend that through the levels of dressage the standard of the horses becomes more consistent. As horses and riders improve past this level, more inconsistent pairs do not progress, reducing the variability within the scores. At the very low preliminary level, a vast range of abilities are present, highlighting the nature of the enthusiastic amateur.

RELATED WORK

Human activity recognition based on the analysis of inertial measurement data has traditionally been one of the core concerns of research in the fields of ubiquitous and wearable computing. It has typically focused on the automatic detection and classification of specific activities a person pursues in their environment [3]. A multitude of technical approaches has been proposed that enable the development of applications in domains as diverse as novel interaction techniques [23], situated support in smart environments [16], occupancy monitoring [22], automated health assessments [14, 34] or health care automation [4, 28, 35] to name but a few. The overall field has matured and standard approaches are now available to researchers and practitioners in the field [8].

Recently, the community has started exploring the use of ubiquitous computing techniques for animal related application domains. Mancini *et al.* explored the design space of human-animal interaction from an ethnographical angle [26] and made concrete suggestions for leveraging sensing and data analysis techniques for future smart environments for animals [27]. Novel interaction approaches have also been the focus of wearable sensing approaches for (rescue) dogs [17]. The foundations for activity recognition in dogs have been laid in [24], where wearable accelerometers and machine learning techniques have been used for continuous logging of dogs' activities. Within the context of activity recognition for horses only very little work has been conducted so far that uses direct sensing and automated data analysis techniques, e.g., [33] where HMMs were used for stride classification.

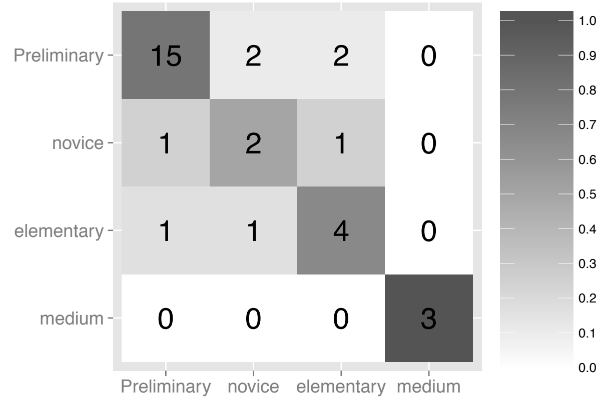


Figure 9: Confusion matrix showing the performance of the SVM classifier for discriminating between test level. The feature set comprised of performance attributes extracted across full tests.

Beyond low level classification of activities, and so far solely focusing on humans, there has been little work that focusses on quality analysis. MusicJacket [38], for example, is a wearable system that aims to support the teaching of posture and technique to novice violin players. In a similar vein, Ahmadi *et al.* [1] assess accelerometry from the swing of a novice tennis player and, through comparisons with an elite athlete's swing, are able to make inferences about the parameters of the swing that represent the skill. Other examples from the sports domain include the assessment of rehabilitation exercises [29] or the SwimMaster system [6], which analyses IMU data to evaluate the efficiency of swimming strokes. ClimbAX [25] is a system developed to automatically assess the performance of rock climbers based on data collected from accelerometers. Through identification of attributes core to rock climbing, parameters were extracted from the data that informed the user of their strengths and weaknesses.

Predominant approaches for semi-automatic analysis of the way a horse moves are assessments of video recordings for the horse (e.g., for lameness detection and analysis [18, 30, 31]). Here recording settings are typically very constrained in order to allow for robust extraction of the kinematics of the horse, which limits the wider applicability to very specific settings. At a professional level, dressage is – on very rare occasions – assessed using high-resolution 3D motion capture. There is a body of work investigating the use of accelerometers to detect lameness in livestock, including horses [9,19,20]. To the best of our knowledge, however, our framework is the first that focusses on automated and objective assessment of dressage exercises using wearable and thus universally applicable sensing, and sensor data analysis.

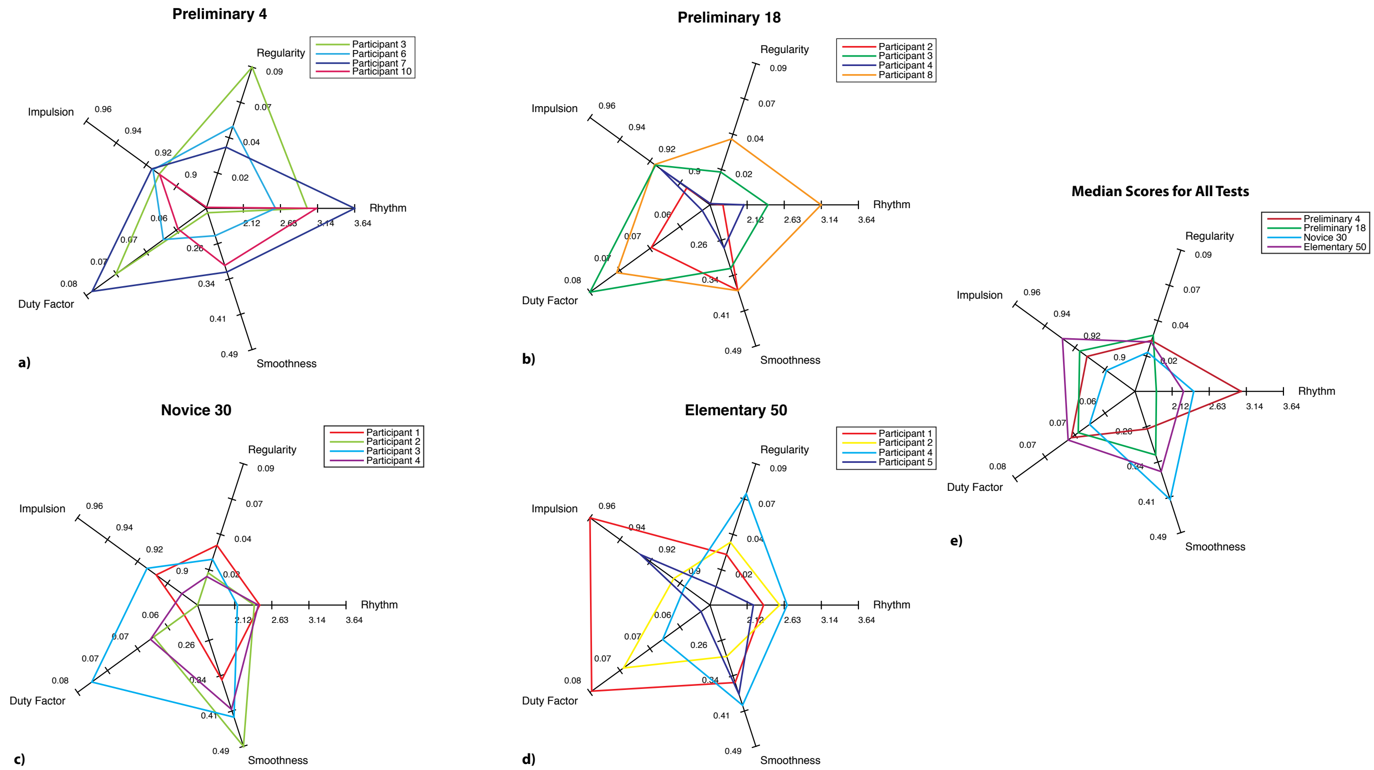


Figure 10: Automatically generated performance attributes for dressage tests (selection from deployment). Smaller values correspond to better performance. For objective rider comparability attributes are grouped according to tests assessed with increasing level of complexity for the overall tests: a) Preliminary 4 (easiest); b) Preliminary 18; c) Novice 30; d) Elementary 50 (hardest; cf. Fig. 1 for explanation of test characteristics). a) to d) show per participant scores. 4 participants have been selected randomly to reduce visual clutter in the spider plots. Considerable differences in performance can be seen, e.g., participant 4 in Preliminary 18 performing better than Participant 8. e) shows median values for each of the test groups, which illustrates how the challenges to the horse and rider generally vary between the different tests. See text for details, best viewed in colour.

CONCLUSIONS

As with any attempt to quantify an inherently complex assessment there are bound to be limitations to the system. Throughout the course of this study we considered accessibility and unobtrusiveness of the system to be key. For this reason we restricted the sensing platform to 4 sensors that could be incorporated into a piece of equipment that the horse would have a prior familiarity with, the brushing boots, see Fig. 3. With a more comprehensive sensing system, a more detailed picture of the horses' movements could have been recorded. This would have given access to assessments of the horses form aside from the movement of the legs, however was seen as too much of an imposition on an amateur rider and horse to maintain wide ranging applicability.

Another implication of our sensing platform was that spatial information about the performance was not available. Positioning within the arena is an important factor of judging, however attaining information of the precision required from IMUs is not currently feasible. Even with advanced GPS chips the spatial resolution is in the order of meters. Given that some movements require consecutive changes of direction within short space, this would not have been adequate.

Summary

Dressage is popular both from a competitive and hobbyist perspective. In the course of our study it was apparent just how many horse owners would take part in small, unaffiliated competitions for the opportunity to get feedback on both their horse and their riding. Like many sports, progress is dependant on deliberate practice, and as such entry into competitions or the hiring of a coach is an important factor in any dressage rider's training. However, these avenues for feedback are costly, both in terms of time and money, which thus often cuts out hobbyists from detailed and quality feedback.

We have developed a sensing and analysis framework that automatically generates quality feedback for dressage exercises. It is based on miniaturised inertial measurement units (IMUs), which are integrated into the standard brushing boots of a horse. IMU data are streamed via bluetooth to a smart phone in the rider's pocket. This sensing approach allows for inexpensive, portable and simple data collection. Using an automated pre-processing and analysis approach our framework generates reliable and reproducible measurements of key performance attributes that are of relevance for describing the characteristics of dressage movements. We use these performance attributes for quality feedback to the riders at varying levels of granularity.

We deployed our framework in a large scale study that involved 21 riders and 23 horses. For a total of 29 dressage tests, performed at varying levels of complexity we generated quality feedback based on the automatically measured performance attributes. The automated feedback system is able to provide specific insights on the quality of the ridden dressage tests and to indicate where and how a rider could improve their performance.

REFERENCES

1. Ahmadi, A., Rowlands, D. D., and James, D. A. Investigating the translational and rotational motion of the swing using accelerometers for athlete skill assessment. In *Sensors, 2006. 5th IEEE Conference on*, IEEE (2006), 980–983.

2. American Horse Publications. 2009-2010 AHP Equine Industry Survey Summary Statistics. online (02-2015): `https://www.americanhorsepubs.org/resources/AHP-Equine-Survey-Final.pdf`.

3. Atallah, L., and Yang, G.-Z. The use of pervasive sensing for behaviour profiling – a survey. *Pervasive and Mobile Computing 5*, 5 (2009), 447–464.

4. Avci, A., Bosch, S., Marin-Perianu, M., Marin-Perianu, R., and Havinga, P. Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey. In *23rd Intl. Conf. on Architecture of Computing Systems (ARCS)*, VDE (2010), 1–10.

5. Axivity. WAX9 – 9-Axis Bluetooth Streaming IMU. online (02-2015): `http://axivity.com/product/5`.

6. Bächlin, M., Förster, K., and Tröster, G. SwimMaster: a wearable assistant for swimmer. In *Proceedings of the 11th international conference on Ubiquitous computing*, ACM (2009), 215–224.

7. British Horse Industry Confederation. BHIC Briefing – Size and Scope of the Equine Sector. online (02-2015): `www.bhic.co.uk/downloads/sizescope.pdf`, 2009.

8. Bulling, A., Blanke, U., and Schiele, B. A tutorial on human activity recognition using body-worn inertial sensors. *ACM Computing Surveys 46*, 3 (2014), 1–33.

9. Chapinal, N., de Passillé, A., Pastell, M., Hänninen, L., Munksgaard, L., and Rushen, J. Measurement of acceleration while walking as an automated method for gait assessment in dairy cattle. *Journal of Dairy Science 94*, 6 (2011), 2895 – 2901.

10. Christine Crawford. Lovedale Riding Academy Website. online (02-2015): `http://wwww.northkaludah.com`.

11. Clayton, H., et al. Time-motion analysis in equestrian sports: the grand prix dressage test. In *Proceedings of the Annual Convention of the American Association of Equine Practitioners*, vol. 35 (1990), 367–373.

12. Dayhoff, M. O., and Schwartz, R. M. A model of evolutionary change in proteins. In *In Atlas of protein sequence and structure*, Citeseer (1978).

13. Fédération Equestre Internationale. *Dressage Handbook Guidelines for Judging*. Fédération Equestre Internationale, Lausanne, Switzerland, 2007.

14. Hammerla, N., Fisher, J., Andras, P., Rochester, L., Walker, R., and Ploetz, T. PD Disease State Assessment in Naturalistic Environments using Deep Learning. In *Proc. AAAI* (2015).

15. Hinchcliff, K., and Geor, R. The horse as an athlete: a physiological overview. *Equine Exercise Physiology: the Science of Exercise in the Athletic Horse* (2008).

16. Hoey, J., Ploetz, T., Jackson, D., Monk, A. F., Pham, C., and Olivier, P. Rapid specification and automated generation of prompting systems to assist people with dementia. *Pervasive and Mobile Computing (PMC) 7*, 3 (2011), 299–318.

17. Jackson, M., Zeagler, C., Valentin, G., Martin, A., Martin, V., Delawalla, A., Blount, W., Eiring, S., Hollis, R., Kshirsagar, Y., and Starner, T. FIDO – Facilitating Interactions for Dogs with Occupations: Wearable Dog-Activated Interfaces . In *Proc. ISWC* (2013).

18. Keegan, K. G., Arafat, S., Skubic, M., Wilson, D. A., and Kramer, J. Detection of lameness and determination of the affected forelimb in horses by use of continuous wavelet transformation and neural network classification of kinematic data. *American Journal of Veterinary Research 64*, 11 (2003), 1376 – 81.

19. Keegan, K. G., Kramer, J., Yonezawa, Y., Maki, H., Pai, P. F., Dent, E. V., Kellerman, T. E., Wilson, D. A., and Reed, S. K. Assessment of repeatability of a wireless, inertial sensor–based lameness evaluation system for horses. *American journal of veterinary research 72*, 9 (2011), 1156–1163.

20. Keegan, K. G., MacAllister, C. G., Wilson, D. A., Gedon, C. A., Kramer, J., Yonezawa, Y., Maki, H., and Pai, P. F. Comparison of an inertial sensor system with a stationary force plate for evaluation of horses with bilateral forelimb lameness. *American journal of veterinary research 73*, 3 (2012), 368–374.

21. Kelmer, G., Keegan, K. G., Kramer, J., Wilson, D. A., Pai, F. P., and Singh, P. Computer-assisted kinematic evaluation of induced compensatory movements resembling lameness in horses trotting on a treadmill. *American journal of veterinary research 66*, 4 (2005), 646–655.

22. Khan, A., Nicholson, J., Mellor, S., Jackson, D., Ladha, K., Ladha, C., Hand, J., Clarke, J., Olivier, P., and Plötz, T. Occupancy monitoring using environmental context sensors and a hierarchical analysis framework. In *Proc. BuildSys*, ACM (New York, NY, USA, 2014).

23. Kim, D., Hilliges, O., Izadi, S., Butler, A. D., Chen, J., Oikonomidis, I., and Olivier, P. Digits: Freehand 3d interactions anywhere using a wrist-worn gloveless sensor. In *Proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology*, UIST '12, ACM (New York, NY, USA, 2012), 167–176.

24. Ladha, C., Hammerla, N., Hughs, E., Olivier, P., and Ploetz, T. Dog's Life: Wearable Activity Recognition for Dogs. In *Proc. UbiComp* (2013).

25. Ladha, C., Hammerla, N. Y., Olivier, P., and Plötz, T. ClimbAX: skill assessment for climbing enthusiasts. In *Proceedings of the 2013 ACM international joint*

conference on Pervasive and ubiquitous computing, ACM (2013), 235–244.

26. Mancini, C., van der Linden, J., Bryan, J., and Stuart, A. Exploring Interspecies Sensemaking: Dog Tracking Semiotics and Multispecies Ethnography. In *Proc. UbiComp* (2012).
27. Mancini, C., van der Linden, J., Kortuem, G., Dewsbury, G., Mills, D., and Boyden, P. UbiComp for Animal Welfare: Envisioning Smart Environments for Kenneled Dogs . In *Proc. UbiComp* (2014).
28. Marcroft, C., Khan, A., Embleton, N., Trenell, M., and Ploetz, T. Movement recognition technology as a method of assessing spontaneous general movements in high risk infants. *Frontiers in Neurology 5*, 284 (2015).
29. Moller, A., Roalter, L., Diewald, S., Scherr, J., Kranz, M., Hammerla, N., Olivier, P., and Plotz, T. Gymskill: A personal trainer for physical exercises. In *Pervasive Computing and Communications (PerCom), 2012 IEEE International Conference on*, IEEE (2012), 213–220.
30. Moorman, V. J., Reiser, R. F., Peterson, M. L. ., Mcllwraith, C. W., and Kawcak, C. E. Effect of forelimb lameness on hoof kinematics of horses at a trot. *American Journal of Veterinary Research 74*, 9 (2013), 1183 – 91.
31. Moorman, V. J., Reiser, R. F., Peterson, M. L. ., Mcllwraith, C. W., and Kawcak, C. E. Effect of forelimb lameness on hoof kinematics of horses at a walk. *American Journal of Veterinary Research 74*, 9 (2013), 1192 – 7.
32. Niggli, W. *Dressage: A Guideline for Riders and Judges*. JA Allen, 2003.
33. Pfau, T., Ferrari, M., Parsons, K., and Wilson, A. A hidden markov model-based stride segmentation technique applied to equine inertial sensor trunk movement data. *Journal of biomechanics 41*, 1 (2008), 216–220.
34. Ploetz, T., Hammerla, N., Rozga, A., Reavis, A., Call, N., and Abowd, G. D. Automatic Assessment of Problem Behavior in Individuals with Developmental Disabilities. In *Proc. UbiComp* (2012).
35. Ploetz, T., Moynihan, P., Pham, C., and Olivier, P. Activity Recognition and Healthier Food Preparation. In *Activity Recognition in Pervasive Intelligent Environments*. Atlantis Press, 2010.
36. Powers, D. M. Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation.
37. Schölkopf, B., and Smola, A. J. *Learning with kernels: Support vector machines, regularization, optimization, and beyond*. MIT press, 2002.
38. van der Linden, J., Schoonderwaldt, E., Bird, J., and Johnson, R. Musicjacket – combining motion capture and vibrotactile feedback to teach violin bowing. *IEEE Transactions on Instrumentation and Measurement 60*, 1 (2011), 104–113.
39. Vicon. 3d motion capturing. online (02-2015): `www.vicon.com`.
40. Witte, T. H., Knill, K., and Wilson, a. M. Determination of peak vertical ground reaction force from duty factor in the horse (Equus caballus). *The Journal of experimental biology 207* (2004), 3639–3648.
41. Xenophon. Περὶ ἱππικῆς *– peri hippikēs (Engl.: On Horsemanship)*. ca. 400 BC.